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An empirical investigation of factors influencing data quality improvement success

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ABSTRACT

While some research has been done to identify the dimensions of data quality and to develop methodologies of improving particular aspects of data quality, the fundamental questions of these methodologies remain vague. This paper tries to fill this gap by empirically analyzing the factors influencing the success of data quality improvements. Hereto, we develop a model for data quality improvement success. This model is evaluated using survey data from 179 respondents. The significance of the model is computed using the maximum likelihood estimation of AMOS. The results show, that organizational implementation success is positively associated with perceived data quality, whereas no significant contribution of data quality projects to perceived data quality could be observed.

Keywords

Information Quality, Data Quality Improvement, Success Factors, Structured Equation Model, Quantitative Research

INTRODUCTION

Information has been recognized as a vital asset to organizations. Ballou, Wang, Pazer and Tayi (1998) define information products, thus assign to information assets a similar value as to physical assets. The value of an information product is influenced by it information quality. Organizations therefore strive to improve the information quality using various techniques. Often "data scrubbing" projects are executed using tools to fix apparent data quality issues. Österle and Winter (2003) identify next to these technical approaches, strategic and organizational aspects as relevant to a holistic information management implementation.

Information quality initiatives are often executed encompassing a data warehouse or smaller data mart project. There has been some research on the effects of data warehousing success which incurs data quality improvement success (Wixom and Watson, 2001). Although, it is common sense that data warehouse projects need to improve data quality, those initiatives often focus only on the data quality relevant for analytical purposes (Jarke, Lenzerini, Vassiliou and Vassiliadis, 2003). Further, data quality is only assured for that specific usage, it is often not fed back to operational usages. Yet information quality has severe impacts beyond the analytical domain. A sufficiently high information quality has to be achieved for operational data (Lee, Pipino, Funk and Wang, 2006). Increasingly, this is considered for master data with adjusted organizational structures and adequate IT support (Kokemüller and Weisbecker, 2009). Even though there are success stories and best practices on how to execute information quality initiatives (e.g. McGilvray, 2008), data quality improvements fail often in achieving a lasting contribution.

There is considerable knowledge among information quality professionals about the key factors to an initiative's success. Still it is based on anecdotes. Practitioners and researchers need to better understand data quality improvements to ensure their lasting success. Askira Gelman (2010) provides a well-grounded theory that helps during the decision which data to improve first. Nevertheless, there has been no academic research that systematically and rigorously analyses the factors influencing data quality improvement success. This study investigates a research model on data quality improvement success using data gathered from 179 IT-professionals.

The paper is structured as follows: We start with a review of relevant literature. In the following section we then develop our research model. Here we describe the data collection and data analysis. Afterwards we discuss our findings before we conclude.

RELATED WORK

Information quality is a multifaceted concept. Wang and Strong (1996) identify 15 dimensions of information quality. These dimensions help in understanding the information's "fitness for use". The latter definition – although not very useful in practice – highlights the goal of information quality improvements: to improve the information quality to a suitable level as required by its use cases. Information quality is especially important, while certainly not limited, to master data. As master data "describes entities that are independent and fundamental for the organization. [Master data] needs to be referenced in order to perform transactions." (International Organization for Standardization, 2009). The quality of master data is therefore multiplied into its referencing transactions. Some improvement strategies for data quality concentrate therefore on the quality of master data, e.g. in master data compliance initiatives (Kokemüller, 2010).

There are several methodologies on how to improve information quality, e.g. from academia (Lee, Strong, Kahn and Wang, 2002; Strong, Lee and Wang, 1997a; Scannapieco, Virgillito, Marchetti, Mecella and Baldoni, 2004) or from a practitioner's perspective (McGilvray, 2008). All include several techniques. While some are specific on which techniques to use as the "Activity-based Measuring and Evaluation of Product Information Quality" methodology that suggests the assignment of process and data responsibilities (Su and Jin, 2004) others for the sake of parsimony require only a selection of strategies and techniques (Batini and Scannapieco, 2006). Only few methodologies provide an evaluation (Batini, Cappiello, Francalanci and Maurino, 2009) moreover, the few evaluations provided are of an ex-post nature. This is reasonable for the evaluation of a single methodology, but provides only limited evidence on the validity of the proposed techniques. A methodology for the improvement of data quality should base itself on ex-ante proven concepts.

It needs therefore to be analyzed how information quality projects compare to organizational changes in terms of the resulting information quality. Yet, information quality is not per se admirable. It rather needs to concur with specific business needs (Capiello and Comuzzi, 2009). Without further dividing the business outcome of data quality it therefore has to generate perceived net benefits. About these effects has been hypothesized by Sheng (2003). While its dependence on the accuracy dimension has been mathematically shown by Askira Gelman (2009), it remains without empirical validation. A rigorously evaluated model is conceived by Wixom and Watson (2001) for data warehousing success. Figure 1 summarizes their model, highlighting significant relations. None of these provide a holistic model for the success of data quality improvements.

The term information often refers to processed and meaningful data present in information systems; data itself only refers to raw facts. In spite of that in the context of information and data quality these two terms are often used interchangeably as it is often impossible to distinguish between the two (Madnick, Wang, Lee and Zhu, 2009). We adhere to that practice and use these terms interchangeably.

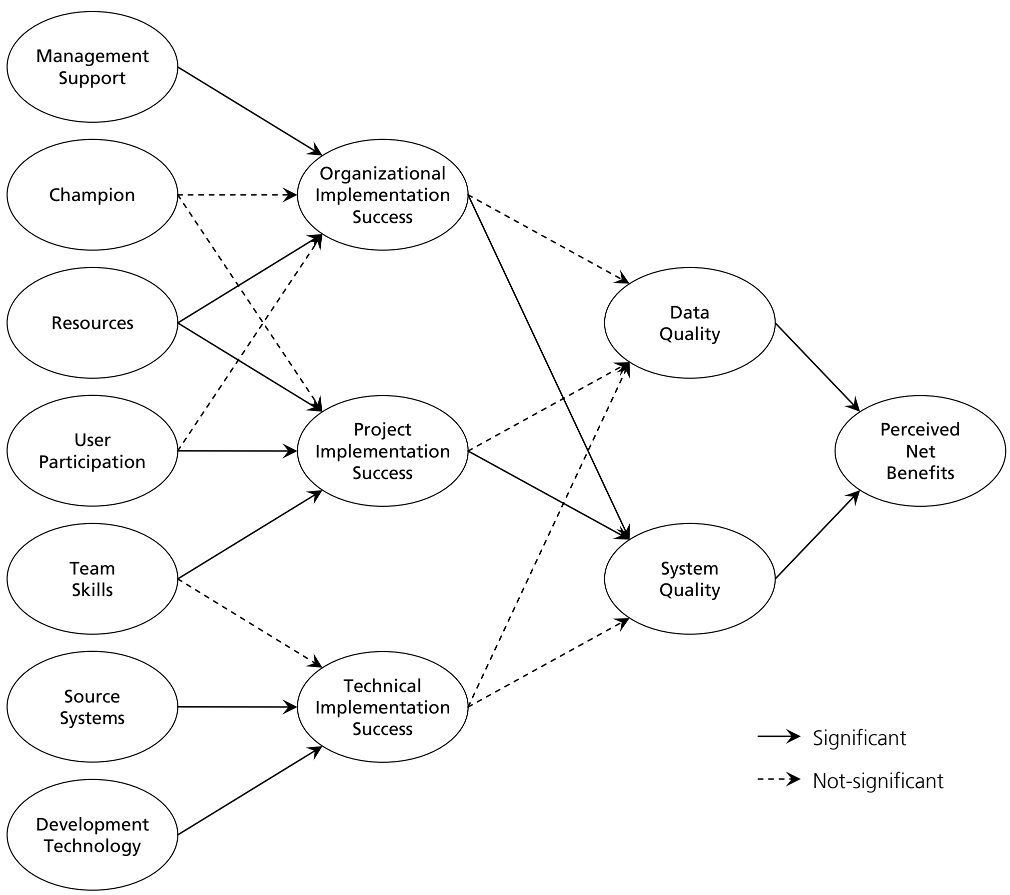

Figure 1: Wixom and Watson's model for data warehousing success

RESEARCH MODEL

We base our research model on the findings of Wixom and Watson (2001). We use equally the structure starting from left with influencing factors which influences success factors. Success factors influence via perceived data quality perceived net benefits.

We alter this model with respect to data quality by including technical capabilities into resources. Due to its non-significance we omit the influencing factor champion. Further we include user participation as a reflective measure of organizational implementation success into this latent variable. We thus omit it as influencing factor and limited the influencing factors to Management Support and Resources. Similar to Wixom and Watson (2001) we do not consider covariances between these influencing factors. Although found non-significant by Wixom and Watson (2001), due to the importance to our model, we include the relationship between the success factors and perceived data quality. Our research model is depicted in Figure 2.

Management Support

Data is handled by its producers, custodians and consumers (Strong, Lee and Wang, 1997a). The involved staff is spread over IT and most business departments of an enterprise. Material master data for example could be created in the research & development or procurement departments and be consumed in sales, accounting and the before mentioned departments. It could be under custody of the IT department.

Consequently, it has been discussed, that management support is important to the success of data quality improvements, as only upper management can allocate cross-departmental resources. In doing so they need to motivate IT and business departments to execute data quality improvements. If a specific data quality improvement involves redesign of processes or responsibilities, we expect it to be more successful if it is backed by management support. We therefore hypothesize:

H1: A high level of management support is associated with a high level of organizational implementation success.

Resources

Resources include money, people and time that are required to complete the improvement (Ein-Dor and Segev, 1978). We additionally understand necessary technologies (e.g. tooling) as fundamental resources. Accordingly, we omit in contrast to Wixom and Watson (2001) development technologies as an isolated influencing factor. Due to this change, the model only consists of reflective measures and is therefore consistent with structural equation modeling's underlying assumptions (Chin, 1998).

Resources are likely to have an impact on data quality improvements, as they are often expensive and require time and people. Further, they may include tasks that need automation, workflows or appropriate user interfaces. Therefore, we hypothesize:

H2a: A high level of resources is associated with a high level of organizational implementation success.

H2b: A high level of resources is associated with a high level of project implementation success.

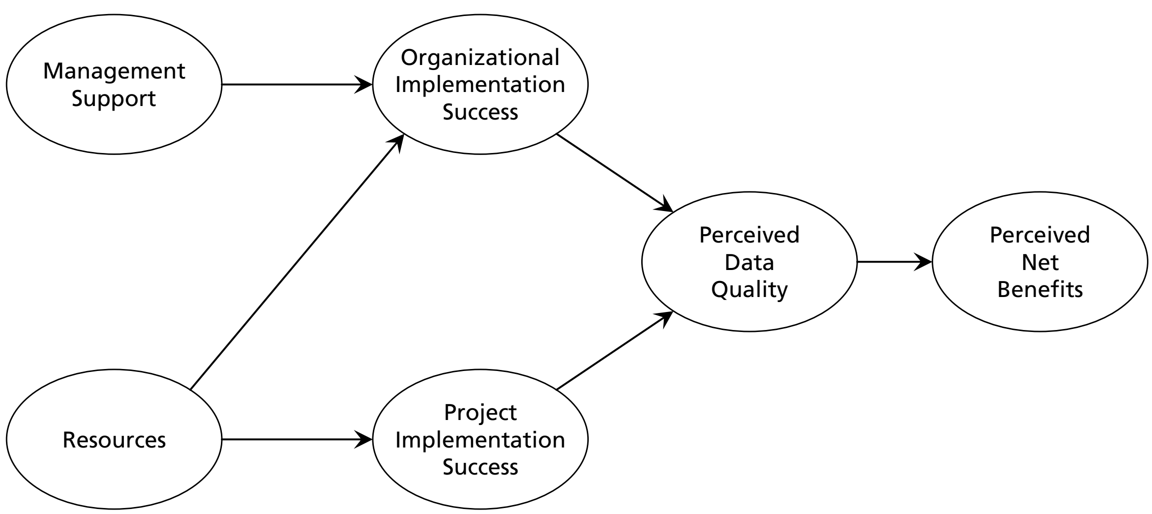

Figure 2: Proposed model for data quality improvement success

Organizational Implementation Success

Data quality correlates with work systems (Alter, 2002). Data quality improvements therefore may change work processes and organizational structures. Anecdotal evidence supports the perception that only if the organizational implementation succeeds a lasting effect of the initiative may be observed. Several best practices have been reported on how a data quality aware work system should be built. Including that the responsibility for data quality should reside to a substantial extent in the business departments. Also data stewards as a responsible central position have been reported as a promising organization of data quality issues (Russom, 2006). Accordingly, we hypothesize:

H3: A high level of organizational implementation success is associated with a high level of perceived data quality.

Project Implementation Success

Data quality projects are regularly executed on a per project basis. The "Total Information Quality Management" Methodology for example mentions as data improvement solutions standardization of data, correction, completion, matching, transformation, and the consolidation of data (English, 1999). These are typical examples of activities executed in a data quality project. We thus hypothesize, that successful data quality projects contribute to improved perceived data quality:

H4: A high level of project implementation success is associated with a high level of perceived data quality.

Perceived Data Quality

Low data quality can have severe impacts, even deadly consequences have been reported (Fisher and Kingma, 2001). As data quality is a multifaceted concept, most methodologies focus on specific dimensions (Batini, Cappiello, Francalanci and Maurino, 2009). To some dimensions automatically evaluable metrics can be defined (Heinrich and Klier, 2008) – e.g. timeliness, completeness, or consistency. Yet, most are only evaluable on a subjective level (Lee, Pipino, Funk and Wang, 2006) – e.g. relevancy, reputation, objectivity, or value-addedness. This effectively is perceived data quality. As Strong, Lee and Wang (1997b) argued, this perceived data quality leads to data not being used or trusted thus not contributing to perceived net benefits. We therefore hypothesize:

H5: A high level of perceived data quality is associated with a high level of perceived net benefits.

Perceived Net Benefits

Data quality is only of value within its usage context. Sheng (2003) proposes hypothesis and specialized constructs on the business impact of data quality. To achieve higher parsimony we summarize these effects according to DeLone and McLean (2003) in one latent variable: perceived net benefits. The optimal data quality can therefore not be given by the data quality's maximum, but only by the maximum perceived net benefit it generates.

RESEARCH METHOD

The proposed constructs have been modeled as reflective latent variables, observed by various indicators. Indicators were associated with residual variances. The indicators were measured in an online survey.

Data Collection

The data was collected in an online survey by the publishers of the "Computerwoche" – a German magazine for IT professionals. The survey collected data from 241 participants and had a total of 179 completed questionnaires returned. The survey was active in 2010 between February 25 and March 5. The complete survey can be found in Computerwoche (2010).

Position	Absolute	Relative
Owner / CEO	16	9%
CIO / IT division manager	16	9%
IT department manager	59	33.1%
IT specialist / IT professional	55	30.9%
Other Position	32	18%
Total	178	

Table 1: Position of respondent

Number of employees	Absolute	Relative
< 49	29	16.3%
50-99	21	11.8%
100-249	35	19.7%
250-499	23	12.9%
500-999	21	11.8%
> 1000	49	27.5%
Total	178	

Table 2: Number of employees

Most of the respondents are IT department managers or IT specialist (Table 1). All company sizes – measured by the number of employees – are represented in the study (Table 2).

Computerwoche reports their findings on 15 separate items without a casual model. The author thanks Computerwoche for allowing him to use their raw SPSS data for the validation of the here proposed model.

Data analysis

An analysis of the causal model was conducted using the maximum-likelihood estimation procedure of "analysis of moment structures" (AMOS) for hypothesis testing. The data were analyzed using AMOS version 18 (Arbuckle, 2009). A structural equation modeling (SEM), a type of multivariate analysis, was applied to confirm the theoretically built model. The estimation and their significance levels for each parameter were obtained. Finally, model diagnostics including measures of model fitness and modification indices of AMOS, were obtained. If indicated, covariances between error terms were added to improve the model. Some model characteristics are displayed in Table 3. As displayed the model fits the data reasonably well.

Goodness of Fit Measure	Value	Recommended threshold	Interpretation
Absolute indices			
CMIN/DF	1.291 (p=0.083)	[0, 2] and p>0.05 (Bagozzi and Yi, 1988)	Meets the recommended threshold
Hoelter's critical N	263	>241 (sample size)	Meets the recommended threshold
RMSEA	0.036	[0, 0.06] (90% confidence)	Meets the recommended thresholds
Incremented indices			
NFI	0.848	>0.9 (perfect fit) (Bentler, 1990)	Does not meet the recommended threshold
CFI	0.958	>0.9 (perfect fit) (Bentler, 1990)	Meets the recommended threshold
IFI	0.961	As close as possible to 1 (Bollen, 1989)	Meets the recommended threshold
Parsimonious indices			
ECVI	0.654	[0.59, 0.765] (90% confidence)	Meets the recommended thresholds

Table 3: Model Fit Measures

The operationalization of the model is shown in Table 4. It summarizes to the latent variables their indicators together with their mean and standard deviation. We operationalize perceived net benefits by measuring the value of data quality in terms of mitigated risks (Batini, Barone, Mastrella, Maurino and Ruffini, 2007). That is if the organization would suffer from low data quality, a higher level of data quality mitigates the risks that the organization suffers. Additionally, if a data quality issue is eminent, than the impact risk is higher – e.g. in terms of required resources, missed opportunities, or fines – if the effort to improve data quality is high.

Indicator	Mean	Std. Dev.
Management Support		
Is Data quality a topic in your organizations that strives IT and business departments?	2.05	1.051
Did your organization execute data quality initiatives in the present or past? (4)	2.57	1.354
Resources		
Does your organization have a budget for data quality initiatives? (2)	2.01	0.635
Do you believe that the budget is sufficient to ensure a sufficient degree of data quality? (4)	2.03	1.055
Do the built in tools of wide spread business software suffice to manage the problems regarding data quality? (3)	2.14	1.081
How good do specialized tools for data quality perform in your opinion?	3.55	1.747
Organizational Implementation Success		
In your opinion, how responsible is the business department to collaborate in ensuring the data quality	2.21	1.442
Is there a central position in your organization that is responsible for data quality? (3)	2.19	0.979
Project Implementation Success		
How do you evaluate the results of your data quality initiatives?	2.82	1.142
Perceived Data Quality		
How do you evaluate the data quality in your organization?	2.62	0.945
Perceived Net Benefits		
Would your business suffer from low data quality?	2.17	1.056
What effort is needed in your organization to ensure and maintain a high level of data quality?	2.53	1.094
All aspects are evaluated on a 6-point Likert scale ranging from very high/good (1) to very low/bad (6). Except those marked by a number in parenthesis (x). Those are measured on a x-point ordinal scale.		

Table 4: Survey items

The model results are shown in Figure 3. Management support and resources contribute to organizational implementation success. Hypothesis H1 and H2a were supported. These factors have unstandardized regression weight of .262 and .886. Resources are also associated with project implementation success (1.247). Yet against expectations, project implementation success had no significant effect on data quality. Hypothesis H4 was not supported.

In this model data quality is only positively influenced by organizational implementation success by a standardized regression weight of 1.639. Hypothesis H3 was supported. As hypothesized perceived net benefits is associated with data quality by a standardized regression weight of 1.098. Thus, hypothesis H5 was supported. The hypothesis are summarized in Table 5.

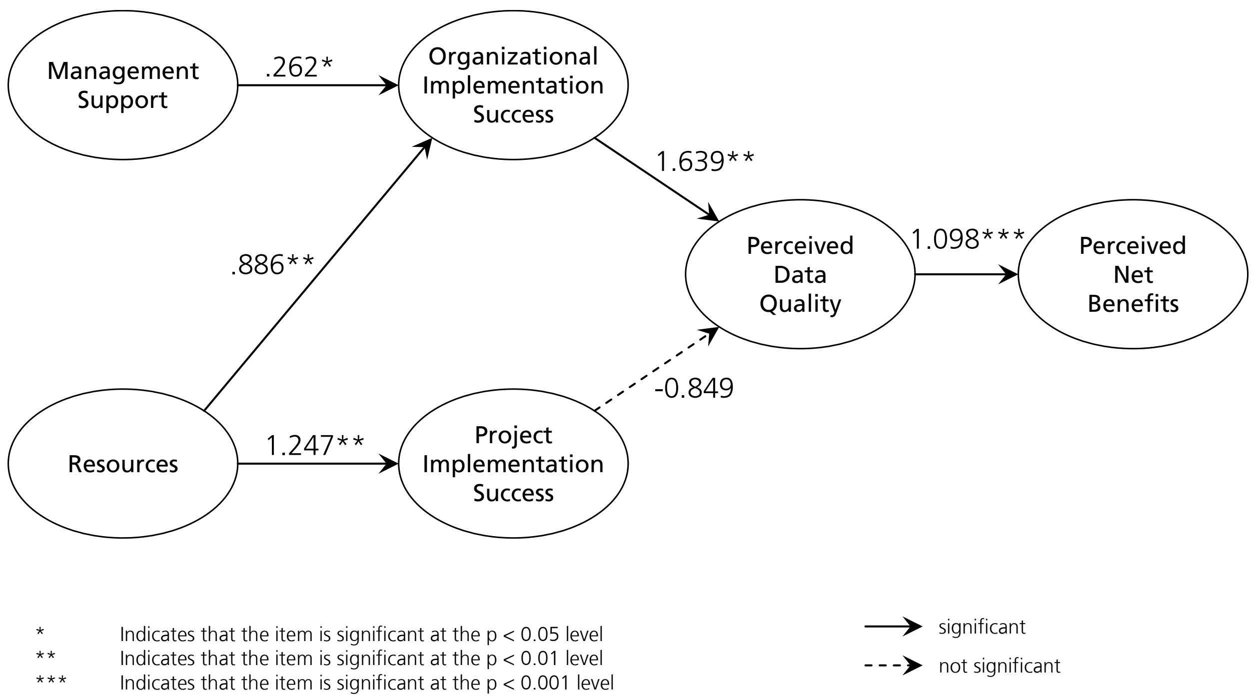

Figure 3: Model results

Number	Hypothesis	Result
H1	A high level of management support is associated with a high level of organizational implementation success.	Supported
H2a	A high level of resources is associated with a high level of organizational implementation success.	Supported
H2b	A high level of resources is associated with a high level of project implementation success.	Supported
H3	A high level of organizational implementation success is associated with a high level of perceived data quality.	Supported
H4	A high level of project implementation success is associated with a high level of perceived data quality.	Not Supported
H5	A high level of perceived data quality is associated with a high level of perceived net benefits.	Supported

Table 5: Hypothesis results

DISCUSSION AND LIMITATIONS

This study based itself on the existent model of Wixom and Watson (2001) on data warehousing success factors. It analyzed the proposed factors for data warehousing success as indicators to the success of data quality improvements.

Perceived Net Benefits

The study showed that data quality has a significant influence on the perceived net benefits. Although, in practice it is often difficult to quantify the benefits of data quality improvements, the perceived data quality has significant impact on its usage. This is no new insight, Wang and Strong (1996) empirically prioritized data quality dimensions. Noteworthy is, that the three most important dimensions (Believability, Value-added, and Relevancy) are all subjectively assed, thus perceived data quality.

This finding supports the importance of subjective measures of data quality. While, due to the low manual efforts required, automatically evaluable (objective) metrics for data quality are desirable, their results will always be limited to less important aspects of data quality.

Perceived Data Quality

Organizational implementation success positively influences perceived data quality. By optimizing processes, responsibilities and decision criteria, perceived data quality can be raised. In practice, those changes are executed in the context of data governance initiatives. As shown, data governance initiatives achieve a significant effect on perceived data quality.

Interestingly, project implementation success has a negative, yet not significant, influence on data quality. This gives clear evidence in decision making, that organizational measures should be preferred over isolated data quality projects. Although, the data does not provide an explanation of this finding, there are several reasons that could explain it: First of all data quality projects do not provide a lasting contribution to data quality, as their outcomes are immediately subject to ongoing deterioration. Furthermore, their outcome may be regarded as a "quick-win" and may lower the motivation for further activities for decisions makers, as first results have been "successfully" achieved. In contrast, the implementation of an effective organization provides lasting results as it stops the ongoing deterioration. Finally, organizational change is more visible to an organization and may thus have a higher impact on the perception of information quality. Still, these reasons would need some additional empirical validation and should be subject of future research. These results give clear advices to practitioners, that isolated data quality projects should be neglected in favor of organizational change.

Organizational Implementation Success

It could be confirmed, that management support and resources positively influence organizational implementation success. Interestingly, resources are more important to the organizational implementation success than management support. This may be due to an inherent link between the two influencing factors, as management support facilitates resources. This casual dependency however was not included in the model as it was neither present in the model of Wixom and Watson (2001).

Project Implementation Success

Likewise, project implementation success is positively influenced by resources. The effect of resources on project implementation success is more dominant than on organizational implementation success. It seems that the finally avoidable project implementation success is more dependent on resources, thus may produce significant savings if neglected or invested in organizational implementation.

It may be that project implementation success has a positive effect on "objective" data quality dimensions, e.g. accuracy. This was not evaluated in this study. Yet the question remains, if this is a promising investment, if there is no significant positive perceived return on investment.

Nevertheless, there was no investigation of further factors influencing the success of data quality improvements. An explorative analysis would be necessary to further investigate relevant still unidentified success factors.

SUMMARY

Current methodologies for data quality improvement are based on ex-post evaluated concepts for the improvement of data quality (Batini, Cappiello, Francalanci and Maurino, 2009). Yet, an ex-ante evaluation of the applied concepts is necessary to properly prioritize the activities executed. This paper developed a model for data quality improvements. The conceived model was evaluated in a survey with 179 respondents. The structured equation model (SEM) could then be evaluated using the maximum likelihood estimation procedure of AMOS. This provides an ex-ante evaluation of the concepts that should be considered in the design of methodologies.

We used the concept of perceived data quality to refer to subjectively evaluated data quality. We showed that perceived data quality is positively associated to perceived net benefits. Against expectations the evaluation showed, that successful data quality projects have no significant impact on the perceived data quality, whereas a successful organizational implementation does have a significant impact on data quality improvements. Both, resources and management support successful implementation of organizational improvements.

This research gives therefore important advices in the setup of a methodology or organizational program for data quality improvements. It provides evidence that data quality projects should be neglected in favor of organizational improvements. It is thus relevant to researchers and practitioners alike.

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